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Spectral Identification of Wild Rice (Zizania palustris L.) Using Indigenous Knowledge and Landsat Multispectral Data

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Spectral Identification of Wild Rice (*Zizania palustris* L.) Using Local Indigenous Knowledge and Landsat Multispectral Data

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Abstract

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Spectral Identification of Wild Rice (*Zizania palustris* L.) Using Local Indigenous Knowledge and Landsat Multispectral Data

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Landsat-7 ETM+ (SLC-off) multispectral satellite imagery was tested to identify and delineate natural stands of wild rice (*Zizania palustris* L.) from other aquatic vegetation growing on area lakes of the Leech Lake Native American reservation in northern Minnesota. Leech Lake is located within the Mississippi River Headwaters drainage ecosystem and contains some of the largest natural stands of wild rice in the country. Local indigenous knowledge; in this case, the knowledge of Ojibwe tribal elders who have traditionally harvested wild rice by canoe for centuries, was utilized to build training data polygons for a supervised classification. By testing several supervised classification algorithms, it was hypothesized that wild rice could be delineated from other aquatic vegetation, but the coarse (30 m X 30 m) spatial resolution of Landat-7 ETM+ multispectral imagery (bands 1-5) would be a limiting factor. Masking upland areas using a 5-category ISODATA Boolean mask improved the classification results of the aquatic emergent vegetation. Maximum likelihood classification yielded a 79.03% accuracy (kappa = 0.6747) and a minimum distance to means classification yielded a 51.61% accuracy (kappa = 0.2092). It was also discovered that by adding band 7 to the stack, the accuracy of the maximum likelihood classifier dropped to 43.55% accuracy (kappa = 0.1891); therefore, band 7 was omitted from the study.

The use of local indigenous knowledge, which includes personal observations and recollection of past harvest years, in conjunction with satellite remote sensing data demonstrated a more precise methodology for identifying culturally important resources on tribal lands. It is recommended that higher spatial resolution imagery be used in conjunction with local indigenous knowledge to identify and delineate species-specific landcover categories such as wild rice. This unique methodology has great potential in many remote regions of the world where indigenous peoples still subsist from the land.

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List of Acronyms

AIANCCWG	American Indian Alaska Native Climate Change Working Group
AISES	American Indian Science & Engineering Society
ATLAS	Airborne TerrestriaL Applications Sensor
BR	Bulrush (*Scirpus spp*.)
CT	Cattail (*Typha spp*.)
DCA	Detrended Correspondence Analysis
EROS	Earth Resources Observation and Science
ETM+	Enhanced Thematic Mapper Plus
FEWS	Famine Early Warning Systems
IEK	Indigenous Ecological Knowledge
IPCC	Intergovernmental Panel on Climate Change
ISODATA	Iterative Self-Organizing Data Analysis Technique
LIS	Line-Intercept Sampling
LLDRM	Leech Lake Division of Resource Management
MAXLIKE	Maximum Likelihood Classifier
MINDIST	Minimum Distance to Means Classifier
MNF	Minimum Noise Fraction
NARSDEP	Native American Remote Sensing Distance Education
NASA	National Aeronautical and Space Administration
NIR	Near Infrared
NTSG	Numerical Terradynamic Simulation Group
OW	Open Water
PCA	Principle Components Analysis
SLC	Scan Line Corrector
TEK	Traditional Ecological Knowledge
TM	Thematic Mapper
UTM	Universal Transverse Mercator
VIS	VISible spectrum
UAV	Unmanned Aerial Vehicles
WR	Wild Rice (*Zizania palustris* L.)
WRS	World Reference System

I. Introduction

Importance of the Study

Many Native American communities in Minnesota, Wisconsin and, Ontario have harvested wild rice for well over 300 years (Vennum 1988). These communities include the Ojibwe (also known as Chippewa), Potawatomie, and Menominee. Today, wild rice continues to be a part of the cultural and economic heritage of tribal communities in these regions. These indigenous communities need to find effective ways to monitor and manage their wild rice crops on area lakes and rivers. Aerial photography is an effective tool, but expensive, especially for multi-temporal analyses. One possible cost-effective technology is satellite remote sensing. This study examines the effectiveness of Landsat multispectral imagery in identifying and delineating natural stands of wild rice from other aquatic emergent vegetation.

Cultural Significance of the Study

In Native American communities that traditionally harvest wild rice, tribal elders play an important role in determining the beginning of harvest season. Local tribal elders, who have harvested wild rice for many years, serve on Ricing Committees that monitor rice stands and determine the opening of the harvest season. In this study, elders play an important role in the remote sensing analysis of wild rice by providing indepth knowledge of the landscape, which can be applied to multispectral analysis techniques. Elders also provide an indepth account of the changes and oral histories associated with the landscape that can enrich the data collection efforts. The use of indigenous knowledge in the remote sensing analysis of wild rice can promote community participation and cooperation between traditional harvesters, science community, and tribal resource managers.

Figure 1. Harvesting wild rice near Walker, Minnesota, 1939 (Minnesota Historical Society).

Project Background

In 1998, a group from NASA Glenn Research Center visited Leech Lake Tribal College to introduce a project idea entitled Native American Remote Sensing Distance Education Prototype (NARSDEP). In the anticipation of the launch of the Landsat-7 satellite with the new ETM+ sensor, NASA included a tribal college as part of their educational outreach. In 1999, the NARSDEP project commenced. NASA Glenn provided the communication satellite link, which connected Leech Lake Tribal College with instructors in the Geography Department at the University of Cincinnati. Six students at Leech Lake Tribal College participated in the distance education pilot study (Bailey et al. 2001a). As a result of NARSDEP, several papers were published on the remote sensing analysis of wild rice, which demonstrated the benefits of this technology to the tribal community. Unfortunately, the project was abandoned in 2001.

Frohn (2005) published a paper entitled *Satellite Mapping and Monitoring of Wild Rice,* which created the first thematic maps of Headquarters Bay in the southeastern region of Leech Lake; the bay known to have some of the largest wild rice beds on the reservation. Though his paper did not include error matrix, the thematic maps generated by Frohn indicated that 100% of the aquatic vegetation in the bay was wild rice. But, tribal elders from the Leech Lake community, those who had harvested wild rice for most of their adult lives on the reservation, knew that there were large stands of cattail and bulrush along with wild rice in Headquarters Bay. This contradiction between remote sensing analysis and indigenous knowledge led to the current study of spectrally identifying and delineating natural stands of wild rice from other aquatic emergent vegetation in the Leech Lake ecosystem.

Research Objectives, Hypothesis and Research Questions

The main objective of this study is to test whether Landsat-7 ETM+ data can identify and delineate natural stands of wild rice from other aquatic emergent vegetation on the area lakes and marshes of the Leech Lake Reservation in northern Minnesota.

The specific objectives of this study are:

1. To identify an effective classification strategy and associated algorithm(s) for delineating natural stands of wild rice.
2. To incorporate local indigenous knowledge of tribal elders into the methods and sampling design.
3. To demonstrate the continued use of the spectral and spatial resolutions of Landsat-7 ETM+ data in SLC-off mode.

The hypothesis of this study is:

H_0: Wild rice cannot be delineated from other aquatic emergent vegetation using Landsat-7 ETM+ imagery.

H_a: Wild rice can be delineated from other aquatic emergent vegetation using Landsat-7 ETM+ imagery.

Research Questions:

1. Can Landsat spatial resolution delineate natural stands of wild rice from other aquatic emergent vegetation?
2. Can Landsat spectral resolution delineate natural stands of wild rice from other aquatic emergent vegetation?
3. Can local Indigenous knowledge contribute to remote sensing techniques in delineating natural stands of wild rice from other aquatic emergent vegetation?

II. Literature Review

Wild Rice (*Zizania palustris*) and its Habitat

Taxonomy. Wild rice is not actually rice *per se*, but is an aquatic grass belonging to the family, Poaceae. The Linnaeus classification for wild rice is *Zizania palustris*. Other species of *Zizania* are *Z. aquatica*, which can be found in wetlands along the eastern coast of the United States, and *Z. texana*, which is an endangered species found only in the riverine wetlands along the San Marcos River in Texas. Both *Z.*

aquatica and *Z. texana* do not yield a robust harvestable grain. There is much confusion between *Z. palustris* and *Z. aquatica* in the literature.

There are two varieties of wild rice (*Z. palustris*) in northern Minnesota, *Z. palustris var. palustris* and *Z. palustris var. interior*. Both varieties exist in Minnesota and are often difficult to distinguish apart. For this study, northern wild rice is referred to as *Zizania palustris*.

Figure 2. View of stands of wild rice (yellowish and distant) and cattail (nearest) in Headquarters Bay facing north.

Vegetation Description. To understand spectral response patterns of vegetation and the unique spectral signatures associated with different species, it is important to know the morphology and growing patterns of the vegetation under analysis (Lillesand et al. 2008). Figure 2 gives a view of adjacent wild rice and cattail stands in the Headquarters Bay of Leech Lake.

Wild rice is an annual aquatic emergent grass that grows in standing water and can reach heights of 2-3 m (~ 6- 9 ft) above the water surface. Its leaves are flat, lance-shaped, 1-5 mm wide and 10-15 mm long. Wild rice is wind-pollinated with a panicle 3-6 dm long and panicle branches 10-20 mm long. The panicle contains both male and female flowers with the male flowers on the lower panicle branches and the female flowers on the upper (Chadde 2002; Eggers and Reed 1997).

The seeds are cylindric ranging from dark brown to black in color, 1-2 cm in length. Wild rice "shatters" meaning that the kernel, when ripened, easily detaches from the panicle branch. This characteristic allows harvesting of the kernels using a canoe.

High winds or heavy rains during harvest season can easily knock the kernels into the water.

Harvest season begins between mid-August to early September and lasts approximately 10-14 days. Wild rice beds on different lakes may ripen at different times, which is monitored by members of the Leech Lake Wild Ricing Committee. In the Ojibwe language, the month of September is called, “Minoominike-giizis” or “wild ricing moon”.

Habitat. Wild rice grows in the marshes, lakes, and slow-moving rivers of the western Great Lakes region. Optimum water depth for wild rice is 45 to 90 cm in depth (1.5 to 3 ft). Saturated, silty, mucky bottoms are prime substrates for growth.

Wild rice grows in dense homogenous stands without rhizomes, which can reach 100’s of hectares in size, and can also line the banks of rivers, marshes, and lakes. The size and homogeneity of larger wild rice stands are advantageous for remote sensing.

Phenology. The spectral response pattern of a particular species or a particular landcover category can change throughout the growing season, which is a function of its lifecycle. Therefore, it is important to understand the different phases of the wild rice lifecycle, especially for multi-temporal analysis. There are seven phenologic stages for wild rice: dormant, submergence, floating leaf, emergence, flowering, seeding, and senescence.

Because wild rice is an annual species, the kernels that fall into the water contribute to next year’s growth. The kernels are non-buoyant and readily sink to the mucky substrate. A small awn on the kernel anchors the seed to the bottom sediment. The kernels lie dormant throughout the winter months; this is called the *dormant stage*. In April, as the days grow longer and ice begins to break up, the kernels begin to germinate. Utilizing the carbohydrates in the kernel, the new plant grows a stem that makes it way towards the surface of the water. This is the *submergence stage*.

As the new plant reaches the water surface towards the end of May, the leaf begins to elongate horizontally across the surface of the water. This is called the *floating leaf stage*. The leaf will grow to approximately 1.0 m in length and is now getting all its nutrients from photosynthesis. This is a fragile stage in the lifecycle of wild rice because wave action and/or wind can uproot the young plants from the substrate.

The stem and leaf strengthen during the next phase, the *emergence stage*. The leaf is now erect out of the water and it begins rapid growth to maturity. By mid-July, the panicle begins forming spikelets where the flowers will emerge; this is the *flowering stage*. The plant continues to reach a height of 2-3 m. By mid-August, after pollination, the kernels begin maturing on the plant; this is the *seeding stage*. When the kernels ripen and are ready to shatter from the stalk, a purplish hue can be seen by looking across a wild rice stand from a distance. This purplish hue is how the elders can tell when the wild rice is ready for harvest. After the seeding stage, the kernels that have fallen into the water have attached to the substrate and will become the following year's crop. By mid-September, the stalks of wild rice begin to lose their green color and eventually turn brown; this is the *senescence stage*. The lifecycle repeats once again.

Benefit to Ecosystem. Much wildlife depends on the existence of wild rice in the northern marshes, lakes, and rivers. Migrating waterfowl such as ducks, geese and swans depend on the kernels as a carbohydrate source as they prepare for their southerly migration. Ducks Unlimited, Inc. lobbies to protect off-reservation wild rice stands as habitat for migrating waterfowl (Ducks Unlimited, 2009). Muskrats depend on the dead stalks of wild rice and cattail for building their winter lodges in the bays and marshes in the late autumn.

Descriptions of Other Dominant Aquatic Emergent Vegetation

In order to spectrally identify and delineate natural stands of wild rice, it is important to understand the morphology and growth characteristics of other dominant aquatic emergent vegetation in the same ecosystem. The two most common species of aquatic emergent vegetation are cattail (*Typha spp.*) and hardstem bulrush (*Scirpus spp.*). Figure 3 displays the three aquatic vegetation categories in the study area.

Figure 3. Photographs of target vegetation categories in Headquarters Bay, Leech Lake (Photos by Michael Price):

a. Bulrush (*Scirpus acutus*)

b. Wild Rice (*Zizania palustris*)

c. Cattail (*Typha latifolia* L.)

Cattails. Broad-leaf cattail (*Typha latifolia* L.) is a perennial herb that grows 1-3 m in height. Long lance-shaped leaves are 1-2 cm wide and extend vertically from the base of the plant. Optimal water depth for cattail is 0.3-0.6 m (~ 1-2 ft). Cattail proliferates by rhizomes, which can create large homogenous stands and floating mats. Narrow-leaf cattail (*Typha augustifolia* L.) is another species of cattail that is found on area marshes, but is less robust than *T. latifolia*.

Bulrush. Hardstem Bulrush (*Scirpus acutus* Muhl) is a perennial herb that grows 1-3 m in height. Bulrush has a dark green vertical stem 0.5-1 cm thick but does not have visible leaves. Rhizomes enable bulrush to colonize open waters. Bulrush grows in thin penetrable homogenous stands and can be found at water depths up to 1.5 m (5 ft) in depth and sometimes deeper. Other species of bulrush found in shallower waters in Minnesota are softstem bulrush (*S. validus* Vahl) and river bulrush (*S. fluviatilis* (Torrey) Gray) and three-squares bulrush (*S. pungens* Vahl).

Other Aquatic Emergent Vegetation. Other aquatic emergent vegetation that can dominate deep marshes and shallow open waters of the Leech Lake reservation are:

- White Water lilly (*Nymphaea odorata* Aiton)
- Yellow Water Lilly (*Nuphar lutea* (L.) Sm.)
- Arrowhead (*Sagittaria latifolia* Willd.)
- Common Reed Grass (*Phragmites australis* (Cav.) Trin.)

<u>Wild Rice and Native Americans</u>

History. Earliest archaeological evidence of the existence of wild rice in the western Great Lakes region dates to 9-10,000 years ago after the retreat of the glaciers (Huber 1999; Pengelly et al. 1995). Archaeological evidence suggests that indigenous peoples began harvesting wild rice within the last 2,000 to 4,000 years (Mather and Thompson 1999; Valppu 1999), although it is unknown as to how early indigenous peoples may have processed wild rice without the use of iron pots and kettles, which appeared in indigenous society during the fur trade era (Vennum 1988).

Cultural Relationship & Traditional Harvesting Methods. The Native Americans of the Great Lakes region are collectively known as the Anishinaabe people. The tribes that make up the Anishinaabe people are the Ojibwe (also known as Chippewa), Menominee, Potawatomie, and Odawa. The name Menominee means "People of the Wild Rice". Beck (1994) documents the early historic and economic relationship between the Menominee people and wild rice. These tribal groups share a common language and traditions. The Odawa, whose traditional homelands are lower and upper Michigan, did not have wild ricing traditions because *Z. palustris* did not grow abundantly in these regions.

The Ojibwe, Menominee, and Potawatomie were expert birchbark canoe builders. It was the canoe that enabled early Native peoples to harvest the ripened kernels of wild rice from lakes, marshes, and rivers. Iron kettles and pots made it possible to parch and process the kernels for long term storage. Processed wild rice can be stored up to five years. This processing method increased the survival rate of Anishinaabe peoples during the harsh winter months (Densmore 1979).

Tribal Economy and Wild Rice. Early Anishinaabe peoples subsisted on the vast stands of wild rice in Wisconsin, Minnesota, and western Ontario. The nutritional and caloric value of wild rice increased life expectancy for those early subsistence communities (Vennum 1998). Modern Native Americans in the United States no longer live subsistence lifestyles, but the traditions of their ancestors are still practiced and honored. Today, instead of birchbark canoes, the Ojibwe use modern canoes for harvesting.

Many Native American reservation communities experience high unemployment and poverty. The average annual income for the Leech Lake reservation is $4,700 with an average unemployment rate of 30.9% (Census 2000). Traditional wild rice harvesters can make up to $2.00/lbs for "green rice" (that is, rice that has not been processed). On a good day, traditional harvesters can average 60-100 lbs/day. This is substantial income for many reservation households. But, according to Leech Lake Ojibwe elder, Wallace Humphrey, "Fewer and fewer young people harvest wild rice these days" (Humphrey 2010).

<u>Remote Sensing of Boreal Wetlands</u>

Remote sensing of wetlands has been thoroughly reviewed in the literature (Ozesmi and Bauer 2002; Rundquist et al. 2001; Silva et al. 2008). Types of sensors, algorithms, and pre-processing techniques relative to wetlands analysis are discussed in detail.

Sensors and Algorithms. In order to conduct an analysis of wild rice using remote sensing technologies, sensor specifications for each earth observing satellite must be initially determined. Four sensor resolutions (spatial, spectral, temporal, and radiometric) are considered in their ability to identify wild rice from satellite. Wild rice has several characteristics that lend to determining the appropriate sensor:

- Spatial - wild rice stands can reach 100's of hectares in size that may be detectable for sensors with coarser spatial resolutions (i.e., Landsat's 30 m x 30 m V-IR resolution).
- Spectral - wild rice grows in dense homogenous stands that may yield spectrally pure signatures.
- Temporal - wild rice is an annual species that has the potential to fluctuate in its growth and distribution patterns because of variable climatic conditions and/or water levels.

The literature states that the two most effective algorithms for analyzing wetland landcover categories are ISODATA and maximum likelihood (Ozesmi and Bauer 2002). Hybrid classifiers such as decision trees and artificial neural networks are demonstrating increasing effectiveness in wetlands analysis. Fuzzy classifiers are also mentioned as showing promise for continuous wetland landcover categories (Silva et al. 2008).

Light Noise and Pre-processing Techniques. Aquatic emergent vegetation presents unique problems for remote sensing. Many species of aquatic vegetation are either submerged, elevated just above the water surface or, like wild rice, elevated 2-3 m above the water surface. Light energy bouncing off the surface of the water creates light noise, which can erode the quality of passive multispectral imagery. Attenuation and path radiance in the atmosphere can also erode data quality. Pre-processing techniques such as minimum noise fraction (MNF) transformation and principle components analysis (PCA) can reduce light noise and atmospheric attenuation in the analysis of aquatic species such as wild rice.

Remote Sensing and Wild Rice. Few remote sensing studies have focused on northern wild rice. Bailey (2001b) conducted the first passive remote sensing study for wild rice in conjunction with the Native American Remote Sensing Distance Education Prototype (NARSDEP) (Bailey et al. 2001a). Frohn (2005) conducted wild rice thematic surveys using Landsat TM and ETM+ sensors. Dixon and Derksen (2000) conducted an active remote sensing analysis of wild rice stands in Manitoba using RADARSAT-1. To date, no further remote sensing studies on wild rice have been published.

<u>Indigenous Knowledge and Remote Sensing Technologies</u>

The integration of indigenous knowledge and remote sensing technologies is a recent development that has gained a lot of popularity. Scientists are discovering that the intimate ecological knowledge that land-based indigenous communities possess of their surrounding landscape has scientific merit (Berkes 1999). Many isolated indigenous communities still lead subsistence lifestyles to varying degrees and their knowledge of the landscape is fortified by these activities. Because of the vast differences in philosophical worldview and methodologies, it is sometimes difficult for the scientific community and traditional indigenous communities to work together on common research goals. Gearheard and Shirley (2007) discuss the successes and failures of cooperative relationships between the scientific community and the arctic indigenous peoples in Nunavut, Canada.

Remote Sensing Applications on Indigenous Lands. The applications of remote sensing technologies can bring benefit to remote land-based indigenous communities. In the Saami territories of Norway, Maynard et al. (2005) demonstrated the application of active remote sensing technology for indigenous reindeer herders by creating maps of vegetation distributions, migratory routes, snow cover, and fire-induced pasture damage. On the Hopi reservation in Arizona, using the Airborne Terrestrial Applications Sensor (ATLAS), Weber and Dunno (2001) mapped and classified riparian vegetation for the Blue Canyon Restoration and Monitoring Project at Moenkopi wash. In Minnesota, Frohn and Price (2003) published a paper on wild rice recovery rates using Landsat TM and ETM+ data after flooding decimated 90% of the crop in 1999. This study assisted the Leech Lake Band of Ojibwe on an insurance claim with the state of Minnesota for wild rice crop losses of that year, in which Leech Lake received their claim.

The timely processing and interpretation of remotely sensed satellite data could mean life or death for human beings living in remote and arid regions of the world. Africa's Famine Early Warning Systems (FEWS) specializes in the detection and measurement of vegetation biomass used in the prevention of widespread famine by identifying oncoming drought conditions early in the year (Jensen et al. 2002).

Indigenous Knowledge: Qualitative vs. Quantitative. One basic assumption of indigenous knowledge is that it is strictly qualitative knowledge, which requires qualitative methods and analysis. Most scientists working in quantitative research scoff at the idea of having to integrate qualitative and quantitative data to derive any meaningful results (personal observation). But, this dilemma is changing. In remote sensing analysis, indigenous people, by assisting with the selection of training sites for a supervised classification, are contributing to quantitative methods and analysis (Naidoo and Hill 2006; Lauer and Aswani 2008; Hernandez-Stephanoni et al. 2006; Maynard et al. 2005).

Integration of Indigenous Knowledge and Remote Sensing Techniques. Although there are numerous applications of remote sensing technologies applied to indigenous lands and tribal natural resources, few studies actually incorporate indigenous knowledge into their methods. Five studies demonstrate how the knowledge of indigenous peoples contributes to quantitative methods and analysis. In all studies, the indigenous people completely grasped the concept of false color imagery and identified familiar sites on the maps.

In the Solomon Islands, Lauer and Aswani (2008) utilized the knowledge of indigenous fishermen to create aquatic habitat categories for the Roviana lagoon.

Using Landsat ETM+ data, maps of indigenously-defined aquatic habitat categories were created to produce a supervised classification with an overall thematic accuracy of 64.5%.

In Paraquay, Naidoo and Hill (2006) conducted a remote sensing analysis of the Mbaracayu Forest Reserve using the rainforest knowledge of Ache tribal hunter-gatherers. In accordance with their knowledge of landscape patterns, the Ache defined seven landcover categories, which were used as training data for a supervised classification resulting in an overall thematic accuracy 60.1%.

In Mexico, Hernandez-Stephanoni et al. (2006) compared local indigenous knowledge classification to DCA (detrended correspondence analysis) survey of a tropical landscape in Quintana Roo. Using Landsat-5 TM imagery, local Mayan farmers provided knowledge to create a seven-category training dataset for a maximum likelihood supervised classification. The thematic accuracy of the landcover map using indigenously-defined samples was 82.3%. The thematic accuracy of the landcover map using DCA methods was 78.01%. This study demonstrates that local indigenous knowledge has the potential to produce accuracies comparable to other ecological survey methods.

In the Arctic, Meier et al. (2006) investigated the effects of the changing sea ice in the Baffin Bay region using microwave remote sensing. Inuit elders and hunters have reported earlier ice break-up, later freeze-up, and thinner ice in their home region. This study combines microwave remote sensing analysis and Inuit knowledge of landcover dynamics to characterize the abrupt changes in arctic sea ice and impacts to human settlement.

III. Data and Methods

Data Description and Processing Environment

The multispectral imagery utilized for this study was Landsat-7 ETM+ acquired on August 22, 2010, which is significant because this date is the approximate beginning of the wild rice harvest season. The data were retrieved from EROS Data Center in Sioux Falls, South Dakota with WRS-2 coordinates at Path 28, Row 27. The scene size is 170 km north-south by 183 km east-west (106 mi x 114 mi).

The spectral bands utilized in this study are band 1 (0.45-0.52 μm), band 2 (0.52-0.60 μm), band 3 (0.63-0.69 μm), band 4 (0.76-0.90 μm), band 5 (1.55-1.75 μm) and band 7 (2.08-2.35 μm) all at 30 x 30 m spatial resolution. Thermal band 6 (10.40-12.50 μm, 60 m x 60 m) and the panchromatic band 8 (0.52-0.90 μm, 15 x 15 m) were not used.

After conducting preliminary image processing using several different software packages including IDRISI Taiga®, ENVI® 4.3, Erdas Imagine® 9.3 and 2010, it was decided that Erdas Imagine 2010 would be the processing environment for this study.

Study Area

The study area for this analysis lies in the eastern region of Leech Lake (Figure 4). This area contains Boy River Bay and Headquarters Bay which are known by local wild rice harvesters to contain some of the largest wild rice stands within the reservation boundary (Humphrey 2010). The Leech Lake Division of Resource Management provided a vector file highlighting the boundary of the reservation (LLDRM 2010). The Boy River, which flows

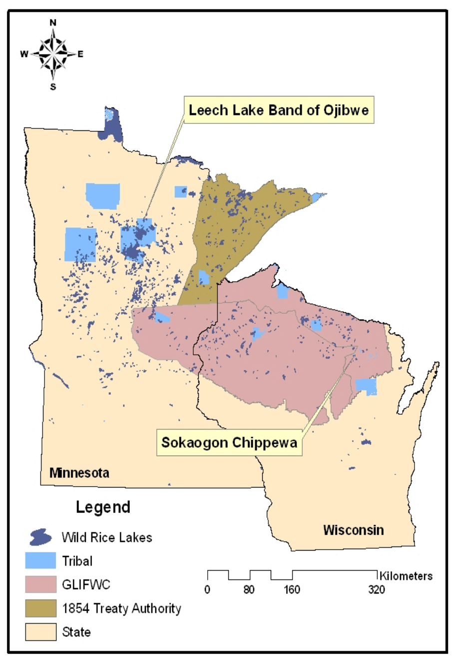


Fig. 4. Map of Leech Lake. GLFWC.

southward out of Leech Lake, serves as the southeasternmost boundary of the reservation.

Landsat-7 SLC-off. The study area contains no scan line errors. On May 31, 2003, the scan line corrector (SLC) onboard the Landsat-7 ETM+ sensor assembly failed. The SLC compensates for the forward motion of the orbiting satellite by correcting gaps and overlaps in the digital imagery. As a result of the failure, the images have data gaps originating from the edges towards the center of the image (U.S. Geological Survey 2008). In the center of the image lies a swath approximately 22 km (13.67 mi) wide, north-to-south, that is void of any scan line errors. Coincidentally, the study area lies within the 22 km swath, so the Landsat-7 ETM+ data were adequate for this analysis.

Classification Scheme

A classification scheme should be exhaustive, mutually exclusive, and hierarchical. "Exhaustive" indicates that every pixel falls into a category; "mutually exclusive" indicates that each pixel falls into one and only one category; "hierarchical" means that two subtle categories should be classified as one; for example, two species of cattail (*T. latifolia* and *T. augustifolia*) are classified as one "cattail" category (Congalton and Green 2009). A classification scheme was developed for the Leech Lake study area that is intended to:

1. delineate aquatic vegetation from open water,
2. identify the three main aquatic vegetation categories in the image,
3. delineate wild rice from other aquatic vegetation with classification accuracy.

Sampling Scheme and Field Data Collection

The sampling scheme includes: 1) developing indigenously defined training data polygons and 2) collecting reference data from the field; both datasets being components of the accuracy assessment error matrix. Because a completely simple random sampling design was not practical for this study area, a hybrid sampling technique, using equalized random sampling and line-intercept sampling, was utilized to collect reference field data. These data will assess how accurately the classification algorithm identified and delineated wild rice from the other categories.

Developing Indigenously-defined Training Data. In March 2010, after examining an unsupervised ISODATA classified thematic map of the study area, Ojibwe tribal elder Wallace Humphrey provided positive identification of the large wild rice stand near Sugar Point Landing on Leech Lake. Because this study focuses on the delineation of wild rice from other aquatic emergent vegetation, it was important to locate other stands of dominant aquatic emergent vegetation in the study area. Mr. Humphrey also noted that large stands of cattails (*Typha* sp.) and Bulrush (*Scirpus* sp.) exist in Headquarters Bay, but these vegetation stands were not apparent in the ISODATA classified image.

Table 1. Category labels for supervised multispectral classification of study area.

Category	Description	Label	Species
1	Wild Rice	WR	*Zizania palustris* L.
2	Open Water	OW	
3	Cattail	CT	*Typha latifolia* L.
4	Bulrush	BR	*Scirpus acutus* Muhl

Using Mr. Humphrey's recollection of the aquatic vegetation in the study area, training data polygons were developed for four categories: wild rice, cattails, bulrush, and open water. Table 1 lists the categories for this analysis.

Reference Field Data Collection. Reference field data was collected during the week of September 10-14, 2010, approximately 3 weeks after the date of imagery, using a motorized boat, a kayak, and a hand-held Garmin® GPSmap 76CSx unit. The boat worked best for open water travel, while the kayak worked best for penetrating stands of aquatic emergent vegetation.

Fifty (50) random sample points were generated using an equalized random sampling function in the Erdas Imagine 2010 software. Using the 5-category ISODATA classified image, this function computed equal numbers of sample points for each ISODATA category. A total of 22 random points were labeled with confidence according to Mr. Humphrey's recollection of the wild rice stands and open water in the study area; the other 28 points were disregarded because their locations were in the "upland" regions of the study area. Another 181 points were collected using the line-intercept sampling (LIS) method in the field, better known as the line-transect method. A total of 203 reference data points were collected (11% random, 89% line-transect). The data points were entered into an Excel spreadsheet with UTM X and Y coordinates and category labels.

<u>Preprocessing of Multispectral Data</u>

Geo-registration of Data. The first step in pre-processing multispectral data is to geo-register the imagery with the processing software that will be used for the analysis. Using Erdas Imagine 2010 software, the Landsat-7 ETM+ images downloaded from EROS Data Center were converted from ".tiff" files to ".img" files. All Landsat-7 imagery are ortho-rectified, meaning that the pixel data are geometrically corrected to a standard ground reference system (WGS-84) which can then be used to generate maps with positional accuracy (Tucker et al. 2004).

Subsets of Study Area. Two subsets were created from the study area: 1) Boy River Bay subset and 2) Headquarters Bay subset. Both Boy River Bay and Headquarters Bay are known to contain some of the largest natural stands of wild rice on the reservation (Humphrey 2010).

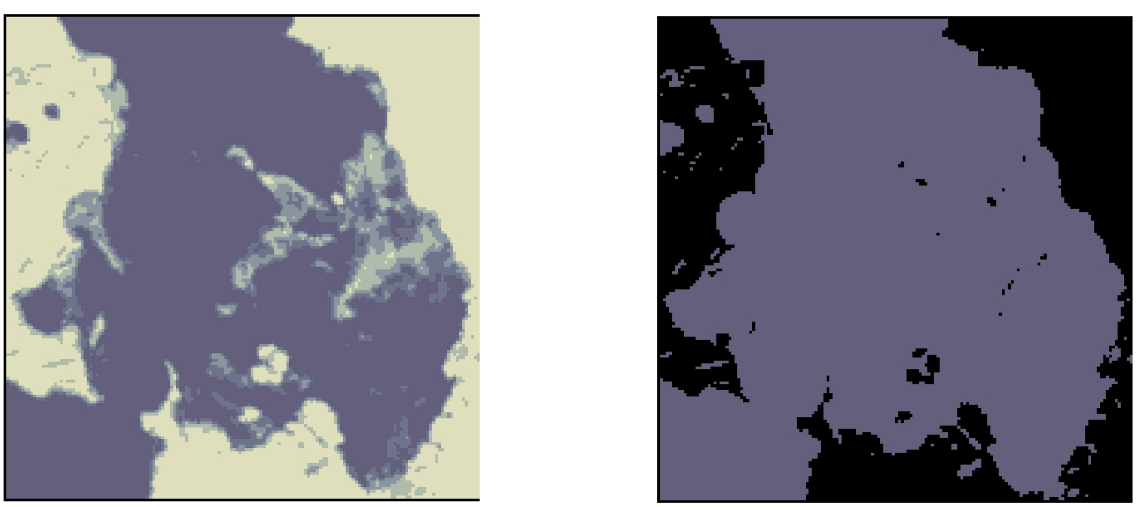
Boy River Bay subset. Boy River Bay is a shallow bay that contains a large wild rice bed surrounded by open water. Ojibwe elder Wallace Humphrey described this bed as a homogenous stand surrounded by vast open water. Traditional harvesters have to paddle by canoe approximately 0.8 km (0.5 mi) from the Sugar Point landing to the rice bed, which can sometimes be treacherous and life-threatening because of gusty winds and high afternoon waves on Leech Lake.

Headquarters Bay subset. Headquarters Bay is located approximately 3.22 km (2.0 mi) south of Boy River Bay. Bear Island provides westerly protection of these wild rice beds from winds and waves action coming off of Leech Lake. There is no readily available public access for canoe harvesters, so many have to tow their canoes in by motorized boat.

Atmospheric and Topographic Correction. Atmospheric correction was not applied to this analysis because this study utilized single day imagery. Correcting for atmospheric attenuation would be necessary for multiple dates of imagery to account for variable atmospheric conditions and haze (Lillesand et al. 2005). The Landsat imagery used for this study was cloud and haze-free. Correcting for topographic attenuation was not necessary because Minnesota is mostly flat.

Upland Data Mask Overlay. Roberts and Gessler (2000) found that by masking out upland vegetation in a wetlands analysis, they reduced the file size, decreased the

Figure 5. The 5-category ISODATA image (L) was used to create the Boolean upland mask (R) in order to separate the upland from the open water and aquatic vegetation in Headquarters Bay.



processing time, and increased the overall accuracy of the image classification. An upland data mask was created from an unsupervised ISODATA classified image of the study area (Figure 5). ISODATA (Iterative Self-Organizing Data Analysis Technique) is a clustering algorithm that arbitrarily groups spectrally-related pixels into categories based on their reflectance values. The analyst specifies the number of categories to be identified, number of iterations to be performed, and the confidence level of the classification. After evaluating numerous categorically classified ISODATA images (categories 2-6), a 5-category ISODATA image performed the best for delineating upland vegetation from water and aquatic vegetation categories. By using the mask, a supervised classification can be conducted using 3-4 landcover categories thus minimizing spectral confusion between upland and emergent vegetation. All ISODATA classifications were performed at 20 iterations with a 95% convergence threshold.

Utilizing a Boolean recoding technique, the 5-category ISODATA image was recoded by assigning a value of "0" to the upland category and a value of "1" to categories 1 thru 4. When converging the data mask with an unclassified image, all pixels in the upland category are multiplied by "0", thus giving a digital number value of "0". Likewise, categories 1 thru 4 are multiplied by "1" by the mask, thus preserving the corresponding pixel value.

<u>Image Classification</u>

Assigning each pixel in a multispectral image to a landcover category in order to create recognizable spatial patterns is called a classification (Lillesand et al. 2008). There are different statistical formulas or algorithms for assigning pixels to landcover categories. It is the job of the analyst to select the classification algorithm(s) that will best characterize the spatial landcover categories that meet the goals of the research. The four supervised classification algorithms tested in this study were: 1) maximum likelihood, 2) Mahalanobis distance, 3) minimum distance to means and 4) parallelpiped.

Maximum Likelihood. Maximum likelihood classifier calculates the probability that a pixel belongs to a certain category based upon the means and variances of the training data. Maxlike assumes that the probabilities are equal for all categories, unless specified by the analyst, and assumes that the data are normally distributed (Lillesand et al. 2008).

Mahalanobis Distance. Mahalanobis distance classifier is based on a covariance matrix that uses variance and covariance to assign pixels to a category. Data samples that are highly varied will lead to similarly varied categories, and vice versa (Lillesand et al. 2008).

Minimum Distance to Means. Minimum distance to means classifier calculates the Euclidean distance between the value of the unknown pixel and the vector mean of each category. After computing the distances, the unknown pixel is assigned to the nearest category. Minimum Distance can be insensitive to the different degrees of variance in the spectral response data (Lillesand et al. 2008).

Parallelpiped. The parallelpiped classifier is a non-parametric algorithm that does not require spectral data to be normally distributed. Parallelpipeds are rectangular areas in spectral space that are defined by the highest and lowest digital number values according to the areas of interest (AOIs) of the training data. Parallelpiped is insensitive to correlation and covariance in the data. For overlapping and unclassified pixels in the data, the maximum likelihood probability decision rule should be applied so that all pixels will be assigned to one and only one category (Lillesand et al. 2008).

<u>Accuracy Assessment</u>

Error Matrix. The most common method of thematic accuracy assessment is the error matrix (also known as the confusion matrix). The error matrix is a statistical computation of how well the chosen algorithm classified each pixel into each landcover category based upon the reference “field” data. The number of landcover categories chosen by the researcher determines the dimension of the error matrix. The columns of the error matrix indicate the number of pixels assigned by the reference data and the rows indicate the number of pixels assigned by the classification algorithm. The error matrix displays overall accuracy, producer and user accuracy, and kappa statistic.

Producer accuracy is the probability that a pixel in the reference data is correctly classified by the algorithm and is calculated by dividing the total number of correctly classified pixels by the total number pixels referenced in the field (columns). User accuracy is the probability that a pixel actually represents the corresponding category on the ground and is calculated by dividing the total number of correctly classified pixels by the total number of pixels assigned by the classification algorithm (rows). The overall accuracy of the classification algorithm is computed by summing up the pixels in the diagonal and dividing by the total number of pixels in the dataset (Congalton and Green 2009).

Kappa statistic. The kappa statistic is a multivariate statistical assessment that summarizes the overall accuracy of the classification using the number of pixels in each column, row, and diagonal of the error matrix. The kappa statistic (also known as "K-hat") is a measure of agreement between remotely sensed data and the reference field data (Jensen 2005).

IV. Results

Upland Data Mask Overlay. The 5-category ISODATA Boolean mask was successful in delineating upland features from the water and aquatic vegetation categories and it also created smaller masks within the vegetation categories around the large stand of cattails. Other ISODATA masks at 2, 3, 4, and 6 categories were created, but none were as accurate at delineating upland from water and aquatic vegetation as the 5-category ISODATA image.

Training Data Limitations. Two limitations were discovered while preparing the training data for analysis: 1) bulrush invisibility and 2) deficiency in cattail and bulrush stands in Boy River Bay study area.

Bulrush Invisibility. In developing training data polygons for the bulrush category, it became apparent that bulrush stands in Headquarters Bay were invisible in the Landsat-7 multispectral data even after multiple radiometric adjustments of hue, saturation, and brightness. Even though 20 reference data points for bulrush were recorded and digital photographs were taken, training data polygons at those locations could not be identified and developed. Therefore, the bulrush category was omitted from the study.

Deficiency in Cattail and Bulrush Stands in Boy River Bay Study Area. The Boy River Bay subset could not be used in this analysis because of the deficiency of large enough stands of bulrush and cattail. A minimum of 9 Landsat pixels is required to create an adequate training data polygon for wetland discrimination, which equals 8,100 m^2 (FGDC 1992). There were several small cattail stands as well as one large bulrush stand in the northern end of Boy Bay that were recorded during reference data collection, but they were not large enough to create training data polygons. According to Ojibwe elder Wallace Humphrey, the largest stands of cattail and bulrush were in Headquarters Bay, not Boy River Bay (Humphrey 2010). As a result, the Boy River Bay study area was omitted from the study.

Classification Results. Four supervised classification algorithms were tested for their ability to identify and delineate wild rice. Those algorithms include: maximum likelihood, Mahalanobis distance, minimum distance to means, and parallelpiped classifiers (Figure 6). During preliminary classification trials, it was discovered that the presence and absence of spectral band 7 had a pronounced negative effect on the classification accuracy using maximum likelihood algorithm. Therefore, two classification sets for each algorithm were performed: one set using spectral bands 1 thru 5 and the second set using spectral bands 1 thru 5 and 7. Table 2 compares the different band combination results using all four algorithms. Because of the lower percentage accuracies, band 7 was not included in any further analyses.

Figure 6. Thematic maps of the tested algorithms in Headquarters Bay. Red = wild rice, light green = cattail, dark green = open water, and black = upland mask.

a. Maximum Likelihood

b. Mahalanobis Distance

c. Minimum Distance to Means

d. Parallelpiped

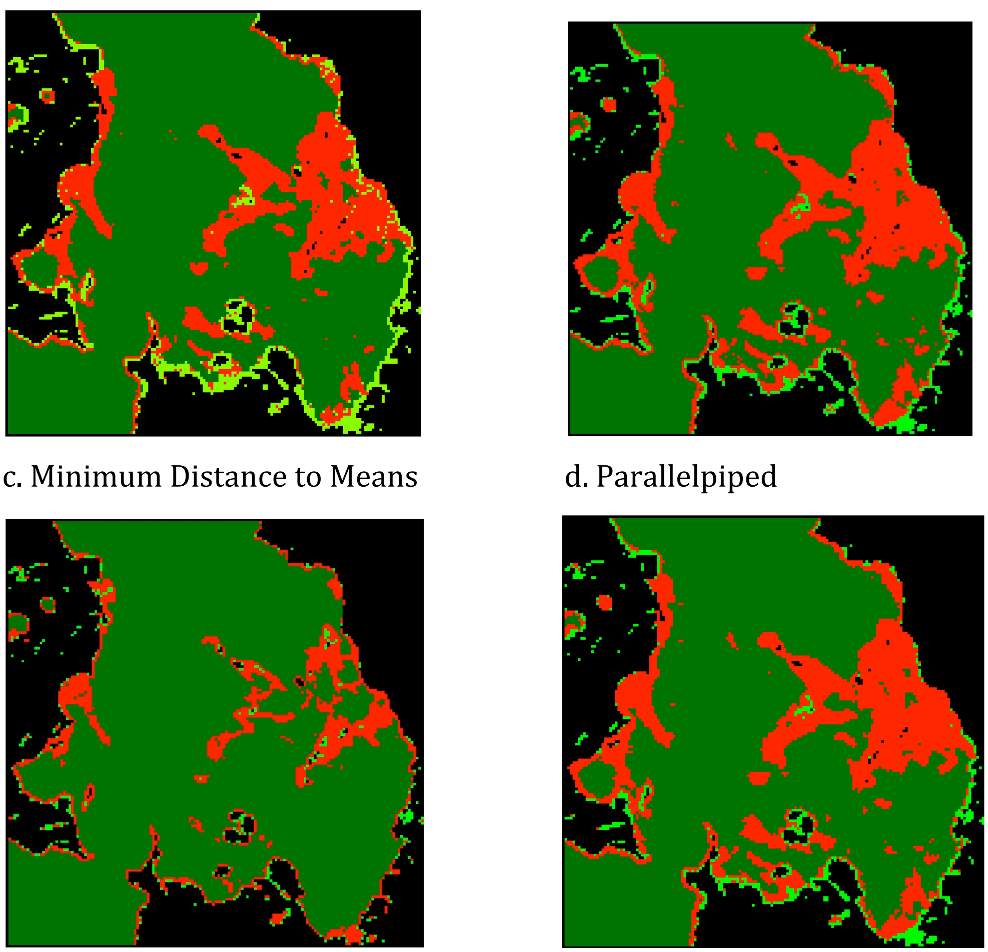


Table 2. Spectral Band 7 Anomaly. Thematic classification accuracies of the Headquarters Bay study area including and excluding Landsat spectral band 7.

	Bands 1-5	Bands 1-5 and 7
Maximum Likelihood	79.03%	43.55%
Mahalanobis Distance	79.03%	09.68%
Minimum Distance to Means	51.61%	51.61%
Parallelpiped	77.42%	11.29%

Maximum Likelihood. In using spectral bands 1 thru 5, Maximum likelihood produced an overall classification accuracy of 79.03% accuracy with a kappa statistic of 0.6747 (Table 3). When spectral band 7 was added to the stack and reclassified, the classification yielded 43.55% accuracy with a kappa statistic of 40.1891.

Table 3: Error Matrix for Maximum Likelihood and Mahalanobis Distance Classifications of the Headquarters Bay study area using spectral bands 1-5 (accuracy results for both algorithms were identical).

	Reference Data			
Classified Data	Cattail	Open Water	Wild Rice	Row Total
Cattail	6	0	0	6
Open Water	0	24	1	25
Wild Rice	10	2	19	31
Column Total	16	26	20	62

Overall Accuracy = 79.03%
Kappa = 0.6747

Accuracy Totals: Maximum Likelihood & Mahalanobis Distance.

Class Name	Reference Totals	Classified Totals	Number Correct	Prod. Accuracy	User Accuracy
Cattail	16	6	6	37.50%	100.00%
Open Water	26	25	24	92.31%	96.00%
Wild Rice	20	31	19	95.00%	61.29%
Totals	62	62	49		

Mahalanobis Distance. Mahalanobis distance algorithm produced identical accuracies and kappa statistic as the maximum likelihood algorithm, although the thematic map produced by Mahalanobis distance contained slightly different pixel assignments as compared to maximum likelihood (Table 3). When spectral band 7 was added to the stack and reclassified, the classification produced an accuracy of 9.68% with a kappa statistic of -0.4395.

Minimum Distance to Means. Minimum distance to means algorithm performed the least well of the four supervised algorithms with 51.61% accuracy with a kappa statistic of 0.2092 (Table 4). When spectral band 7 was added to the stack and reclassified, the classification yielded results identical to the classification using bands 1 thru 5.

Table 4: Error Matrix for Minimum Distance to Means Classification of the Headquarters Bay study area using spectral bands 1-5.

	Reference Data			
Classified Data	Cattail	Open Water	Wild Rice	Row Total
Cattail	0	0	0	0
Open Water	2	26	14	42
Wild Rice	14	0	6	20
Column Total	16	26	20	62

Overall Accuracy = 51.61%
Kappa = 0.2092

Accuracy Totals: Minimum Distance to Means

Class Name	Reference Totals	Classified Totals	Number Correct	Prod. Accuracy	User Accuracy
Cattail	16	0	0		
Open Water	26	42	26	100.00%	61.90%
Wild Rice	20	20	6	30.00%	30.00%
Totals	62	62	32		

Parallelpiped. Also known as the “box decision rule,” Parallelpiped algorithm produced an overall accuracy of 77.42% with a kappa statistic of 0.6492. When spectral band 7 was added to the stack and reclassified, the classification yielded 11.29% accuracy with a kappa statistic of -0.4103 (Table 5).

Table 5: Error Matrix for the Parallelpiped Classification of the Headquarters Bay study area using spectral bands 1-5.

	Reference Data			
Classified Data	Cattail	Open Water	Wild Rice	Row Total
Cattail	5	0	0	5
Open Water	0	24	1	25
Wild Rice	11	2	19	32
Column Total	16	26	20	62

Overall Accuracy = 77.42%
Kappa = 0.6492

Accuracy Totals: Maximum Likelihood

Class Name	Reference Totals	Classified Totals	Number Correct	Prod. Accuracy	User Accuracy
Cattail	16	5	5	31.25%	100.00%
Open Water	26	25	24	92.31%	96.00%
Wild Rice	20	32	19	95.00%	59.00%
Totals	62	62	48		

V. Discussion

Error Matrix. The maximum likelihood algorithm, and subsequently Mahalanobis distance, performed the best in this study with an overall accuracy of 79.03% accuracy (kappa = 0.6747). Parallelpiped algorithm produced an overall accuracy of 77.42% (kappa = 0.6492) and the minimum distance to means algorithm produced the lowest overall accuracy of 51.61% (kappa = 0.2092).

Both maximum likelihood and Mahalanobis distance algorithms produced identical accuracies and kappa statistics. Such a small reference dataset (n < 30 per category) may have precipitated these identical results. In examining the thematic maps of both algorithms, they contain slight differences in pixel assignments that aren't readily observable. A more robust reference dataset may have produced slightly different statistical results in the error matrix but, upon close examination and comparison of the thematic maps, the performance of both maximum likelihood and Mahalanobis distance algorithms produce near identical classifications in delineating wild rice, cattail, and open water categories.

Producer/User Accuracies for Each Algorithm. For all four algorithms, spectral confusion existed between wild rice and cattail. The higher overall classification accuracies were the result of how well the algorithms delineated open water from both aquatic vegetation categories. The error matrix gives detailed information about how the algorithm performed in identifying and delineating wild rice from other categories in the form of producer and user accuracies.

For the maximum likelihood and Mahalanobis distance algorithms, although 95% of wild rice has been correctly classified by the algorithm as wild rice (producer accuracy), only 61.29% of the pixels classified as wild rice on the map are actually wild rice in the field (user accuracy). According to the error matrix, 33.00% of wild rice category was misclassified as cattail, but none (00.00%) of the cattail category was misclassified as wild rice. For open water, the producer and user accuracies were 92.31% and 96.00% respectively, which means that the two algorithms did exceptionally well in delineating open water from all aquatic vegetation categories (Table 1).

For the minimum distance to means algorithm, the producer and user accuracies for wild rice were 30% and 30%, respectively. The error matrix indicates that 70% of wild rice was classified as cattail. With 16 data points referenced as cattail category, cattail could not be classified and delineated from wild rice by the minimum distance to means algorithm. For open water, the producer and user accuracies were 100% and 61.90%, respectively. According to the error matrix, there is spectral confusion between open water and wild rice. According to the user accuracy estimates, 34.00% of the area referenced as open water was misclassified as wild rice (Table 2).

For the parallelpiped algorithm, the producer and user accuracies for wild rice were 95.00% and 59.38%, respectively. According to the error matrix, 35.00% of wild rice category was misclassified as cattail, but none (00.00%) of the cattail category was misclassified as wild rice. For open water, the producer and user accuracies were 92.31% and 96.00%, respectively, which means that parallelpiped performed exceptionally well in delineating open water from all aquatic vegetation categories (Table 3).

Spectral Band 7 Anomaly. When spectral band 7 was added to the stack and reclassified, all classification results exhibited a decrease in overall accuracy except for minimum distance to mean, which maintained the same overall accuracy and kappa statistic (Table 4). There is little information in the literature on which mid-infrared bands are optimal for wetland vegetation discrimination. Lillesand et al. (2008) defines the middle infrared regions (bands 5 = 1.55-1.75 μm, band 7 = 2.08-2.35 μm) as the water absorption bands because they are sensitive to internal plant moisture content. Jensen et al. (1993) found that the middle infrared bands were important for discriminating different types of coastal wetlands from adjacent uplands. Sharma et al. (1995) researched the optimal spectral band combinations for discriminating oilseed crops, orchards, scrubs, acacias and forests. They found an improvement in crop discrimination by adding a mid-infrared band (mostly band 5) to the visible bands (band 1-2-3) and near-infrared band (band 4), but no significant improvement was observed when both mid-infrared bands (bands 5 & 7) were used together. One possible suggestion for this decrease in thematic accuracy by spectral band 7 inclusion is "mid-infrared overkill". Because the study area is a permanently flooded marsh environment, oversensitivity to water absorption by bandstacking the data may classify thinner stands of wild rice as open water. According to error matrices, wild rice was misclassified as open water by Mahalanobis distance, parallelpiped, and minimum distance to means classifiers by 84%, 81%, and 34% respectively, but open water misclassified as wild rice was 47%, 46%, and 30%, respectively.

Bulrush Invisibility. Bulrush (*Scirpus acutus* Muhl) is one of the three dominant aquatic emergent vegetation species in the Headquarters Bay study area according to Ojibwe elder Wallace Humphrey (Humphrey 2010). However, training data polygons could not be developed because the bulrush stands were invisible in the remotely sensed pixel data. One suggestion for bulrush invisibility has to do with the plant's morphology. Because Bulrush has dark green (0.5-1 cm thick) vertical stems and does not have visible leaves branching off the stalk, light easily passes through the canopy and reflects off the water surface. Because of the dark green color and the morphological characteristics of bulrush, passive sensors may detect mostly the reflectance of light bouncing off the water and passing through the canopy. Thus, a multispectral satellite image of a bulrush stand may appear like a contaminated "open water" signal. Higher spatial resolution or radar sensors such as synthetic aperture radar (SAR) or Lidar may have more success in identifying bulrush stands in open water ecosystems. Bulrush invisibility is advantageous to identifying wild rice stands at this spatial and spectral resolution.

Upland Data Mask Assessment. The hybrid approach using an ISODATA-generated upland mask and a supervised classification proved effective in delineating the three categories (wild rice, cattail, and open water) from upland features. Thus, by masking out the upland features, the thematic maps could spatially identify cattail stands along the shores of the lake delineated from the upland.

According to thematic maps, the upland mask also created masking polygons within the aquatic vegetation categories. Two possibilities may have accounted for this upland "masking" within vegetation categories:

1. floating cattail mats can support the growth of sphagnum moss and other peatland vegetation which can resemble upland characteristics, or
2. there is actual upland in the middle of the large cattail stand.

The research team wasn't able to penetrate and verify the interior of the larger cattail stand although shrubs and peatland vegetation were visible from the boat. The 5-category ISODATA upland mask, along with personal observations, suggests that there are upland characteristics inside the large stand of cattail.

Visual Interpretation of Thematic Maps. Although the classification statistics revealed spectral confusion between wild rice and cattail, visual interpretation of the thematic maps reveals spatial information of the landcover categories within the study area. In examining the thematic map generated by the maximum likelihood algorithm, basic assumptions about the distribution of each aquatic vegetation category can be inferred (Figure 6a). It is apparent that cattail stands line the edges of the bay while wild rice inhabits deeper open waters in greater abundance. Thus, it can be argued that wild rice can grow in cattail niches, but cattail cannot grow in wild rice niches. Thus, both plants appear to be water depth dependent.

VI. Conclusion

Addressing Research Questions

Research Question 1: *Can Landsat spatial resolution delineate natural stands of wild rice from other emergent vegetation?*

Using the thematic map at 30 x 30 m spatial resolution, Ojibwe elder Wallace Humphrey was clearly able to make visual interpretations and identify points of interest of the study area on Leech Lake. Clear thematic delineations of wild rice and cattail stands were apparent on maps generated by maximum likelihood, Mahalanobis distance and parallelpiped algorithms. The Landsat spatial resolution may be adequate for the larger homogenous stands of wild rice and cattail on area lakes, but smaller stands and areas of thin vegetation may not be accurately detectable and the problem of mixed pixels will arise.

With a pixel area of 900 m^2, it was difficult to develop training data for cattail in Headquarters Bay study area; in fact, training data polygons could not be developed in the Boy River Bay study area because of the sparseness of cattail stands. With higher spatial resolution imagery (smaller surface area per pixel), more robust training data can be developed, especially when targeting species-specific landcover categories.

Research Question 2: *Can Landsat spectral resolution delineate natural stands of wild rice from other emergent vegetation?*

The accuracy assessment data indicated that open water was spectrally delineated from the two aquatic vegetation categories with good accuracy. However, there was spectral confusion between the wild rice and cattail categories to varying degrees with all the tested algorithms.

With the omission of spectral band 7 and using only spectral bands 1 thru 5, all supervised algorithms, with exception to minimum distance to means, exhibited increased overall classification accuracy of the study area.

It is recommended that further analysis of the spectral data, in conjunction with higher spatial resolution data, be conducted to identify spectral bands or regions of the electromagnetic spectrum that are ineffective in identifying and delineating wild rice from other aquatic emergent vegetation in permanently flooded area conditions.

Research Question 3: ***Can local Indigenous knowledge contribute to remote sensing techniques in delineating natural stands of wild rice from other emergent vegetation?***

The knowledge of indigenous elders provided the necessary information in which to build training data polygons for supervised classification of the study area. Elders Wallace Humphrey and Bob Jourdain contributed to this analysis by:

1. characterizing the species composition and location of the study area,
2. providing historical (ancillary) information about the study area such as flood or drought conditions, good or bad harvest years, presence or absence of specific vegetation.

Fig. 7. ISODATA classification of Boy Bay, Leech Lake.

Upon examining a false color map, Mr. Humphrey quickly identified the large wild rice stand in the Boy River Bay study area and described it as pure wild rice with no other coexisting species (Figure 7). Based upon Mr. Humphrey's observations, the different categories generated by the

ISODATA classification algorithm indicate density patterns as opposed to coexisting vegetation niches. This type of information is valuable for characterizing the variance in an associated multispectral dataset. From this study, it is recommended that more time be allocated for elders and local rice harvesters to practice interpreting the false color images and classified thematic maps of the study area.

Indigenous knowledge may also play an important role in providing ancillary data such as periods of drought or flooding for the study area, as these environmental variations will impact the spectral response of the vegetation and surrounding landscape. This *a priori* knowledge will assist in creating more accurate thematic maps for wild rice.

Future Recommendations

More Robust Reference Dataset. On several days during the week of September 10-14, 2010, the winds and wave action were too high to safely get a kayak onto the bay for data gathering. So, only three days were available for data collection, which yielded only 203 total reference data points. As a result of the lack of cattail and bulrush stands in Boy River Bay, 121 reference data points were omitted from this study. Also, because of the bulrush invisibility, another 20 data points for the bulrush category in Headquarters Bay study area were omitted. As a result, only 62 reference data points were utilized for classification accuracy analysis of three landcover categories (16 = cattail, 20 = wild rice, 26 = open water). A more robust data set, with at least 30 data points for each category, would have given more statistical confidence in the analysis.

Analysis of Different Phenological Stages of the Wild Rice Lifecycle. For this analysis, Landsat-7 multispectral image data August 22, 2010 was chosen to characterize the abundance and distribution of the wild rice crop for that year. This data was chosen because the growth phases in all vegetation categories were complete and the robustness of the wild rice crop was at its maximum.

Other phenological stages in the lifecycle of wild rice may yield more optimal results for delineation studies. For example, the floating leaf stage in the wild rice lifecycle may produce more pronounced delineation estimates as opposed to the harvest stage where spectral confusion existed between wild rice and cattails. Best et al. (1981) reported that different phenological stages in 10 species of hydrophytes yielded significant differences in reflectance values. Cattail is a perennial species that remains vertically erect year after year, whereas wild rice has a visually distinct floating leaf stage (Figure 8). During these time periods, delineation features may be at their maximum while wild rice is still floating on the surface of the water or in a particular stage of development. One possible complication with the floating leaf stage is the possibility of detecting a strong water signal as a result of the young leaf floating directly on top of the water. The mixing of water and aquatic vegetation signals will diminish the overall reflected radiation in all sensor band regions of the electromagnetic spectrum.

Fig. 8 Floating leaf stage of wild rice. Photo by Michael Price.

Higher Resolution Sensors and Landsat Continuity Mission

A new generation of commercial multispectral sensors are emerging with higher spatial, temporal, spectral, and radiometric capabilities, which may prove to be valuable for aquatic vegetation studies, including wild rice. The new WorldView II satellite has 8 spectral bands including the new coastal blue (400-450 nm), yellow band (585-625 nm), red edge band (705-735 nm), and near infrared 2 band (860-1040 nm) (DigitalGlobe 2011). These extra bands in the visible and near infrared spectrum may prove invaluable in delineating upland and wetland vegetation. Also, the WorldView II satellite sensor has a 46 x 46 cm spatial resolution and a revisit period of 1.1 days that will provide more precise characterizations of edge boundaries and distribution patterns of landcover categories.

The advantage of refining the analytical techniques using Landsat multispectral data is because of the continuous Landsat landcover data archive. If wild rice detection and delineation are successful using Landsat, tribal nations that traditionally harvest wild rice will have access to 30 years of 30 x 30 m multispectral data. The Landsat Data Continuity Mission (LDCM), scheduled to launch in December 2012, will continue to grow the global multispectral imagery archive (http://ldcm.nasa.gov), which will be important for multi-temporal change detection analysis and climate change impacts.

Unmanned Aerial Vehicles (UAVs): The Future of Vegetative Remote Sensing

Satellite remote sensing has its limitations in obtaining optimal multispectral imagery for vegetation analysis. Limitations for satellite remote sensing are timeliness, atmospheric attenuation, repair, and maintenance. In regards to timeliness, satellites have fixed orbital paths and speeds that produce predictable revisit times. Phenological changes in vegetation can occur within days, which doesn't always align with satellite flyovers. Also, the time of day for obtaining optimal multispectral data is not an option for high altitude orbital satellites. Clouds, haze, light scatter, and path radiance are prevalent distortions in satellite-derived multispectral imagery. Image correction is usually required especially for multi-temporal studies. Repair and maintenance are not conventional options for orbital satellites. A perfect example is the Landsat-7 scan line corrector (SLC) malfunction on May 31, 2003 in which all Landsat imagery acquired after that date were permanently affected. There is no way to easily repair an orbital satellite at 750 km above the earth's surface. Thus, the search for cost-effective and optimal digital imagery acquisition continues.

The use of unmanned aerial vehicles (UAVs) offers an alternative to cost-effective vegetative remote sensing and may soon compete with, if not replace, orbital and manned airborne satellite sensor platforms in the future. Berni et al. (2009) demonstrated that low-cost UAVs could produce quantitative remote sensing data products with spatial (20 cm), spectral (0.4 to 0.8 μm), and temporal resolutions comparable to manned airborne sensors. Different types of UAVs are rotary-wing (helicopter) and fixed-wing platforms, and both carry an array of optical sensors, GPS navigation, and video capabilities.

Advantages of UAV remote sensing are: 1) rapid deployment capability for phenological timeliness, 2) remote area accessibility, 3) low altitude flying, 4) longer flight durations over study area, 5) lower fuel costs, 6) slower flight speeds, and 7) variable spatial resolutions from same sensor. The disadvantages of UAV remote sensing are: 1) sampling height distortions, 2) sampling pattern distortions, 3) take-off and landing requirements, 4) motor vibrations affecting image quality, and 5) restrictive FAA flight regulations for larger UAVs. Figure 9 gives examples of different types of unmanned aerial vehicles (UAVs).

Fig. 9. Unmanned aerial vehicles. Courtesy of NASA.

UAV remote sensing technologies have been used for numerous types of landcover and agricultural studies. Laliberte et al. (2010) developed an ortho-rectification procedure for creating large mosaics of small-footprint UAV images of rangelands in southwestern Idaho. Götogan et al. (2010) utilized a rotary-winged UAV equipped with low-cost sensor suite for monitoring aquatic weed infestation in an inaccessible marsh habitat near Sidney, Australia. Herwitz et al. (2004) demonstrated the “loitering” capability of a UAV hovering over a coffee plantation in Hawaii for 4 hours awaiting cloud-free imagery on a cloudy day. Rango et al. (2006) demonstrated that data products from numerous types of platforms including spaceborne, airborne, UAVs and ground-based boom photography, can work in unison for in-depth rangeland analysis. For forest fire detection and monitoring, Ollero et al. (2006) examined the potential for UAV multispectral applications in the "before-during-after" scheme to firefighting. Casbeer et al. (2005) developed a path-planning algorithm for deploying multiple UAVs for large wildfire scenarios in inaccessible mountain terrain. Figure 6 displays four different types of UAVs.

For many tribal nations, much of their territories are in remote regions of the country and, oftentimes, many of these areas are difficult to access such as the wild rice stands of the Leech Lake reservation. Low-cost flyovers using UAVs can benefit tribal nations in the monitoring and management of their natural resources such as buffalo rangeland management, caribou migratory routes, forest resources, salmon habitat, or wild rice.

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